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OPTIMIZATION OF PROCESS PARAMETERS OF FDM PART FOR MINIMIIZING ITS DIMENSIONAL INACCURACY

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ABSTRACT

Fused deposition modelling (FDM) is one of the fast growing 3D printing techniques due to its ability to build functional parts of complicated geometry in least possible time without incurring any extra cost due of absence of tooling. Despite of having various advantages there is limitation in terms of dimensional accuracy as the quality of final FDM part depends on many parameters which include layer thickness, orientation, raster angle and etc. In this regard, the present study incorporates the parametric optimization of FDM fabricated ABS (acrylonitrile-Butadiene-Styrene) part for improving its dimensional accuracy. Three important factors that are considered for optimization are raster angle, air gap and raster width. In order to reduce experimental runs, face cantered central composite design (FCCCD) is used. Analysis of variance (ANOVA) is used to test validity of the models and empirical models relating response and process parameters are developed. Anderson- darling (A-D) normality test is used to establish its practicality in engineering application. The major reason for inaccuracy of the part is irregularities and shape error. Finally, composite desirability function (CFD) is used to find the optimal parameter setting for building the ABS part with minimum overall deviations in dimension.

KEYWORDS: Fused Deposition Modelling, ABS, FCCCD, Raster Angle, ANOVA & Desirability

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Original Article

INTRODUCTION

Fused deposition modelling (FDM) is the most commonly used 3D printing due to its ability to produce complex part geometries from three dimensional CAD (computer aided design) model in least possible time as stated by Mohamed et al. (2015). It doesn't involve any tooling problem and also there is no need for specific process plan. The part is produce by layer-wise deposition of semi-molten material from nozzle of FDM machine. Gebhardt (2012) states that, first a nozzle will deposit the support material onto table or platform and then part material is deposited over the support structure following three axes motion of nozzle over build table. The deposited material cools, hardens, and bonds to the layer beneath it. This process is repeated up to the last layer. Once the part building is complete then the support material is removed by breaking it, called as post processing. Different performance measures of FDM techniques such as dimensional accuracy, surface roughness, mechanical strength, build time, material properties and post-processing defines the final use of the part. These performance measures can be improved by controlling the primary process parameters directly affecting the final

part build. The important process parameters are raster angle, raster width, layer thickness, air gap and part orientation and their interactions. Although, FDM process is an efficient and reliable process but it has got its own limitations. These limitations include poor dimensional accuracy, poor surface finish and poor strength and less compatible materials available. Thus, optimization of process parameter is very essential for improvement in various performance measures. In this direction, an attempt has been made in the present study to optimize the process parameters for improvement in dimensional accuracy by minimizing the deviations in overall dimension. Generally, the dimensions of FDM processed part are different from the dimensions of input CAD model because of shrinkage factor, machine inaccuracy and etc. Earlier work reveals that shrinkage is only along the length and width of the build part. Also, a positive deviation is also observed along the thickness direction. All of these dimensions can be combined together into a single representative unit that is volume and change in volume can be minimized (Sood et al., 2009). The main disadvantage of this approach is that it may be possible that some dimensions show large deviation and some may show small deviation from the desired values. The combined effect may decrease change in volume. But actual fabrication of part should be made in such a manner that all dimensions show minimum deviation from desired value simultaneously at a common factor level setting. The different performance measures or response considered in this work are change in length (ΔL), width (ΔW) and thickness (ΔT). Also, three important process parameters are considered for optimization i.e. Raster angle, air gap and raster width.

LITERATURE REVIEW

Over last many years, different modelling methods like Taguchi method (Anitha, 2001) artificial neural networks (ANNs) (Khan and Mahapatra, 2007; Roy, 2010) and fuzzy inference system (FIS) (Shipley and Coy, 2009; Assadi and Cheragi, 2009.) and etc. have been used by many researchers to find best parameter setting in which these part should be manufactured for minimum deviations in dimensions. Sood et al. (2009) studied the influences of five process parameters i.e. part orientation, road width, layer thickness, air gap and raster angle on dimensional accuracy of FDM fabricated ABSP400 part using gray Taguchi method. They concluded that to reduce the deviation between fabricated part and CAD model dimension, layer thickness of 0.178 mm, part orientation of 0º, raster angle of 0º, road width of 0.4564 mm and air gap of 0.008 mm should be used. Further, they have employed gray relational grade (GRD) to convert three responses (percentage change in length, width and thickness) into one response. Also, in order to predict these three responses more accurately due to their non-linearity, they used artificial neural network (ANN) and fuzzy logic. Lastly, the best parameter combinations were obtained. A study made by Es Said et al. (2000) have shown that anisotropic behaviour on mechanical properties is caused mainly due to raster orientation when ABSP400 samples are built on FDM 1650 machine. Wang et al. (2007) also pointed out that dimensional accuracy of fabricated part depended on build orientation and depositing thickness. The differences in dimensional accuracy in the different building directions were the results of different deposition patterns. Nancharaiah et al. (2010) have applied Taguchi method and ANOVA technique to address the key factors influencing the dimensional accuracy of ABS parts. They concluded that layer thickness and air gap significantly affected the accuracy of FDM parts. However, their study doesn’t give optimum settings of layer thickness, road width, raster angle and air gap. Zhang and Peng (2012) established empirical relations between process parameters (wire-width compensation, extrusion velocity, filling velocity, and layer thickness) and dimensional error and deformation of FDM fabricated ABS part using Taguchi method combined with fuzzy comprehensive evaluation. They reported that the optimal process parameter values for dimensional error were: wire-width compensation 0.17 mm, extrusion velocity 20 mm/s, filling velocity 30 mm/s and layer thickness 0.15 mm. In case of deformation, the optimum combinations of the parameters were: wire-width compensation 0.17 mm, extrusion velocity 25 mm/s, filling velocity 20 mm/s and layer thickness 0.30

mm. In their study, only the best combination of the selected process parameters was obtained. Taguchi method was used by Sahu et al. (2013) to study the effects of layer thickness, orientation, raster angle, raster width and air gap on part accuracy. To optimize dimensional accuracy they have developed prediction model based on fuzzy logic and Mamdani method. Finally, they concluded that the value of average percentage error of less than 4.5% was obtained from the laboratory experiment which agreed well with the predicted response. However, the use of fuzzy inference system (FIS) requires developing rules. Therefore, it needs appropriate expertise knowledge and experience. In the present work, response surface methodology (RSM) is combined with composite desirability function (CDF) to understand the effect of process parameters and their interaction on accuracy of dimensions and to optimize the process parameters to achieve minimum overall deviations i.e. change in length, width and thickness in combined. Desirability function approach is one of the most widely used methods in industry for the optimization of multiple response processes but this technique has not been investigated in this concerned area.

METHODOLOGY

FDM is a 3D printing technique in which the final part is obtained by layer-wise deposition of part material one over another. Literature survey suggested that quality of generated FDM part is depended on various control factors. Thus, the present study considers three important factors i.e. raster angle (A), air gap (B) and raster width (C) each at three different levels. They are briefly defined as follows (Stratasys, 2004):

- Raster angle: It is a angle between raster and X-axis of build table.
- Air gap: It is the gap between two adjacent rasters on same layer.
- Raster width: It is the width of raster pattern used to fill interior regions of part curves.

For performing the experiments, RSM (Response surface method) is used. RSM is a mathematical technique in which response or output is affected by several input variables and the objective is to optimize (maximize or minimize) the response. A quadratic model is used to explain the behaviour of the system. Regression analysis is done by 'Minitab R16'. To reduce the number of experimental runs face centred central composite design (FCCCD) is used. FCCCD consists of eight star points, six cube points and six central points as shown in Figure 1.

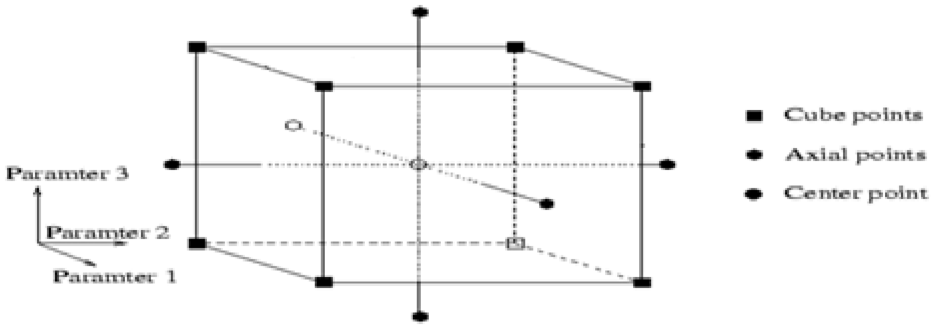

Figure 1: Face Centred Central Composite Design (FCCCD)

Maximum and minimum value of each factor is coded into +1 and -1, respectively. The FCCCD design involves 20 experimental observations at three independent input variables. Table 1 shows both coded and actual values of the three factors parameters and their possible ranges. The result of experimental matrix is shown in Table 2 in coded form. Parts for experiment are fabricated using FDM Vantage SE machine. The material use for part fabrication is ABSP400.

Table 1: Selected Factors and Their Levels

Factors	Symbol	Units	Levels		
			-1	0	+1
Raster angle	A	Degree (º)	0º	30	60
Air Gap	B	Mm	-0.004	0.000	0.004
Raster width	C	Mm	0.4064	0.4564	0.5064

Three readings each for length, width and thickness are taken in the sample and mean is taken as representative value for each of these dimensions. Dimensions are measured using digital vernier calliper having least count of 0.01 mm. Measurements show that measured length (L), width (W) and thickness (T) is always more than the CAD model value. Relative change in dimension is calculated using Eq. 1.

$$\Delta X = (X - X_{CAD}) / X_{CAD} \tag{1}$$

Where, X is the measured value of length or width or thickness, X_{CAD} represent the respective CAD model value and ΔX stands for relative change in X.

Table 2: Experimental Results as Per FCCCD Design

Exp. No.	Factors (Coded Units)			Relative Change in Dimensions		
	A	B	C	ΔL	ΔW	ΔT
1	-1	-1	-1	0.0007667	0.0040952	0.0250476
2	1	-1	-1	0.0017667	0.0072381	0.0285714
3	-1	1	-1	0.0016667	0.0050476	0.0257143
4	1	1	-1	0.0024333	0.0042857	0.0257143
5	-1	-1	1	0.0022500	0.0019048	0.0261905
6	1	-1	1	0.0030000	0.0102381	0.0314286
7	-1	1	1	0.0018667	0.0057143	0.0250476
8	1	1	1	0.0028667	0.0107619	0.0281905
9	-1	0	0	0.0026667	0.0047619	0.0259524
10	1	0	0	0.0027667	0.0119048	0.0271429
11	0	-1	0	0.0016667	0.0047619	0.0292000
12	0	1	0	0.0012667	0.0050476	0.0298095
13	0	0	-1	0.0003333	0.0040952	0.0259524
14	0	0	1	0.0006667	0.0035238	0.0283333
15	0	0	0	0.0018667	0.0062857	0.0276190
16	0	0	0	0.0013333	0.0053333	0.0285714
17	0	0	0	0.0012000	0.0044381	0.0276190
18	0	0	0	0.0017667	0.0062857	0.0295238
19	0	0	0	0.0010833	0.0054762	0.0295238
20	0	0	0	0.0011333	0.0049524	0.0288571

Once the response surface method is used to establish the effect of process parameters on the responses, composite desirability is used for optimization of process parameters. Desirability is a multiple response method given by Derringer and Suich (1980), is an attractive method for optimization of multiple quality characteristic problems. The method makes use of an objective function, D(X), called the desirability function and transforms an estimated response into a scale free value (di) called desirability. The desirable ranges are from zero to one (least to most desirable respectively). The factor settings with maximum total desirability are considered to be the optimal parameter conditions. The simultaneous objective function is a geometric mean of all transformed responses as shown in Eq. 2:

$$D = d_1 \text{ x } d_2 \text{ x } d_3 \text{ x } \ldots\ldots. \text{ x } d_n)^{1/n} = \prod_{i=1}^{n}(d)^{1/n} \quad (2)$$

Where, n is the number of responses in the measure. Thus, composite desirability is used to obtain the optimum process parameter to optimize each of the responses individually and combined.

RESULTS

ANOVA is used for analysing the result of full quadratic model considered. Significance of related terms and interactions is established using p values as obtained from ANOVA table. If p value (also known as α error) is less than 0.05 for a term or interaction then the corresponding term or interaction is significant. However, lack of fit value must be greater than 0.05 because it indicates any term left out of model is not significant and developed model fits well. Based on analysis as given in Table 3, the model was found to be suitable for dimensional accuracy with regression p-value less than 0.05 and lack of fit more than 0.05.

Table 3: Anovas Table for Dimensional Accuracy

Source	DOF	Relative Change in Dimensions											
		ΔL (Relative Change in Length)				ΔW (Relative Change in Width)				ΔT (Relative Change in Thickness)			
		SS	MS	F	P	SS	MS	F	P	SS	MS	F	p
A	1	0.000001	0.000001	11.55	0.007	0.000052	0.000052	55.29	0.00	0.000017	0.000017	21.3	0.00
B	1	0.000000	0.000000	0.37	0.555	0.000001	0.000001	0.72	0.42	0.000004	0.000004	4.41	0.06
C	1	0.000001	0.000001	11.98	0.006	0.000005	0.000005	5.74	0.04	0.000007	0.000007	8.32	0.02
A*A	1	0.000005	0.000005	46.76	0.000	0.000012	0.000023	24.12	0.00	0.000013	0.000008	9.81	0.01
B*B	1	0.000000	0.000000	0.46	0.512	0.000004	0.000001	0.86	0.38	0.000002	0.000004	5.42	0.04
C*C	1	0.000002	0.000002	16.68	0.002	0.000007	0.000007	7.79	0.02	0.000003	0.000003	4.14	0.07
A*B	1	0.000000	0.000000	0.00	0.986	0.000006	0.000006	6.81	0.03	0.000004	0.000004	4.89	0.05
A*C	1	0.000000	0.000000	0.00	0.986	0.000015	0.000015	15.94	0.00	0.000003	0.000003	3.66	0.08
B*C	1	0.000001	0.000001	4.79	0.053	0.000005	0.000005	5.28	0.04	0.000001	0.000001	0.74	0.40
Error	10	0.000001	0.000000			0.000009	0.000001			0.00001	0.000001		
Total	**19**	**0.00001**				**0.000119**				**0.00006**			

Table 3 show that A (raster angle) and C (raster width) are significant for relative change in length (ΔL) and relative change in width (ΔW). Interaction terms of B x C is significant for ΔL whereas all interaction terms are significant for ΔB. For thickness, significant terms includes all linear terms and interaction of terms A x B and A x C. From the above analysis it can be concluded that the dimensional accuracy is mainly affected by raster angle and raster width and air gap don't impart significant effect on dimensional accuracy. Anderson–Darling (AD) normality plot results are shown in Figure 2 for respective response. Since p value of all the normality plots is found to be above 0.05, it signifies that residue or errors follows normal distribution. To determine the individual significant term, t-test was performed at 95% of confidence level and final response surface equations for relative change in length, width and thickness (ΔL, ΔW and ΔT) are given as per equations. (2) - (4).

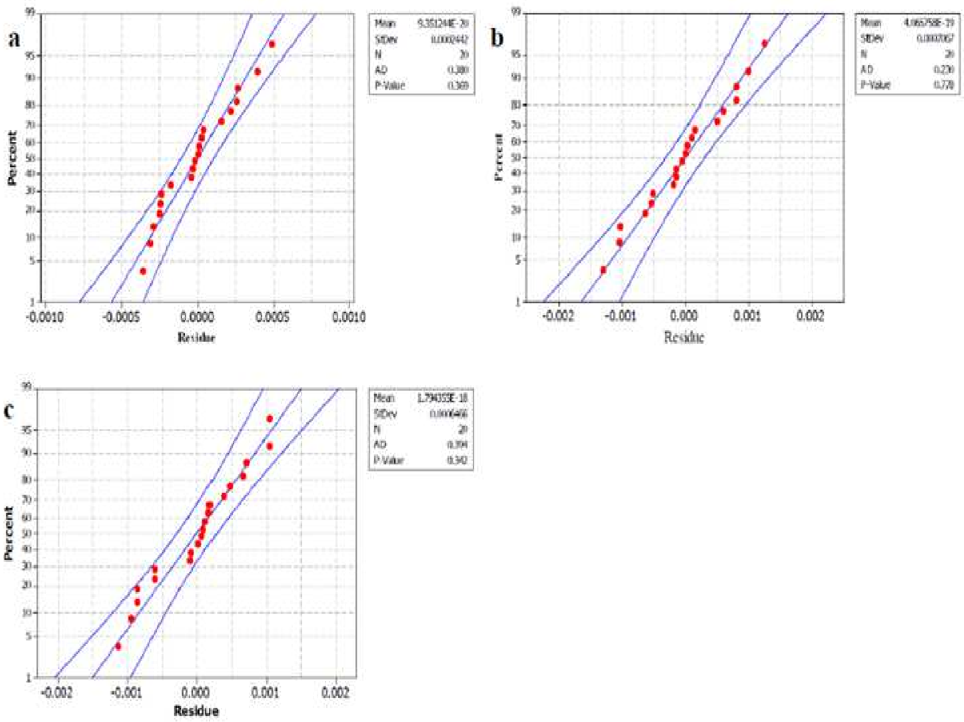

Figure 2: A-D Plot for (A) Relative Change in Length, ΔL (B) Relative Change in Width, ΔW and (C) Relative Change in Thickness, ΔT

$$\Delta L = 0.00136985 + 0.000361667\ A + 0.000368333\ C + 0.00138788\ A^2 - 8.28788E\text{-}04\ C^2 - 2.60417E\text{-}04\ (B \times C) \tag{2}$$

$$\Delta W = 0.00545654 + 0.00229048\ A + 0.000738095\ C + 0.00288485\ A^2 - 0.00163896\ C^2 - 8.98810E\text{-}04\ (A \times B) + 0.00137500\ (A \times C) + 0.000791667\ (B \times C) \tag{3}$$

$$\Delta T = 0.0284691 + 0.00130952\ A + 0.000819048\ C - 0.00169654\ A^2 + 0.00126061\ B^2 - 7.02381E\text{-}04\ (A \times B) \tag{4}$$

Typical response surface plots for significant interactions are shown in Figure 3. Variation in relative change in length (ΔL) with varying of the significant factors is explained in Fig. 3(a). It can be observed that ΔL increases with increase in air gap whereas, with increase in raster width it first increases and starts decreasing towards the end. Figure 3 (b) - Figure 3 (d) explains the variations of relative change in Width (ΔW) with various significant factors obtained from Table 3.8. It can be observed that with increase in raster angle ΔW continuously increases. ΔW continuously decreases with increase in air gap. The variation in ΔT (relative change in thickness) is shown in Figure 3 (e). Increase in raster angle (A) cause increase in ΔT but towards the end it slightly decreases. Also, decrease in ΔT can be seen from Figure. The reason for decrease in ΔT is that raster when deposited over another raster with increased air gap causes it to shift more towards previous raster decreasing the overall thickness. Increased in length and width are observed nearer to the machine tolerance limit. Increased length is observed also because of surface irregularities and bump present while part building In the process of part fabrication first a contour is provided and within that raster filling is done. Also, between the raster then will be air gap provided (positive or negative) and it may lead to irregularities creating oversize or undersize parts. For the negative air gap a bump formation occurs and it further affects the part accuracy. The reason for increased in width is same as that of increased length. However, the increased in thickness is because of irregularities and shape error.

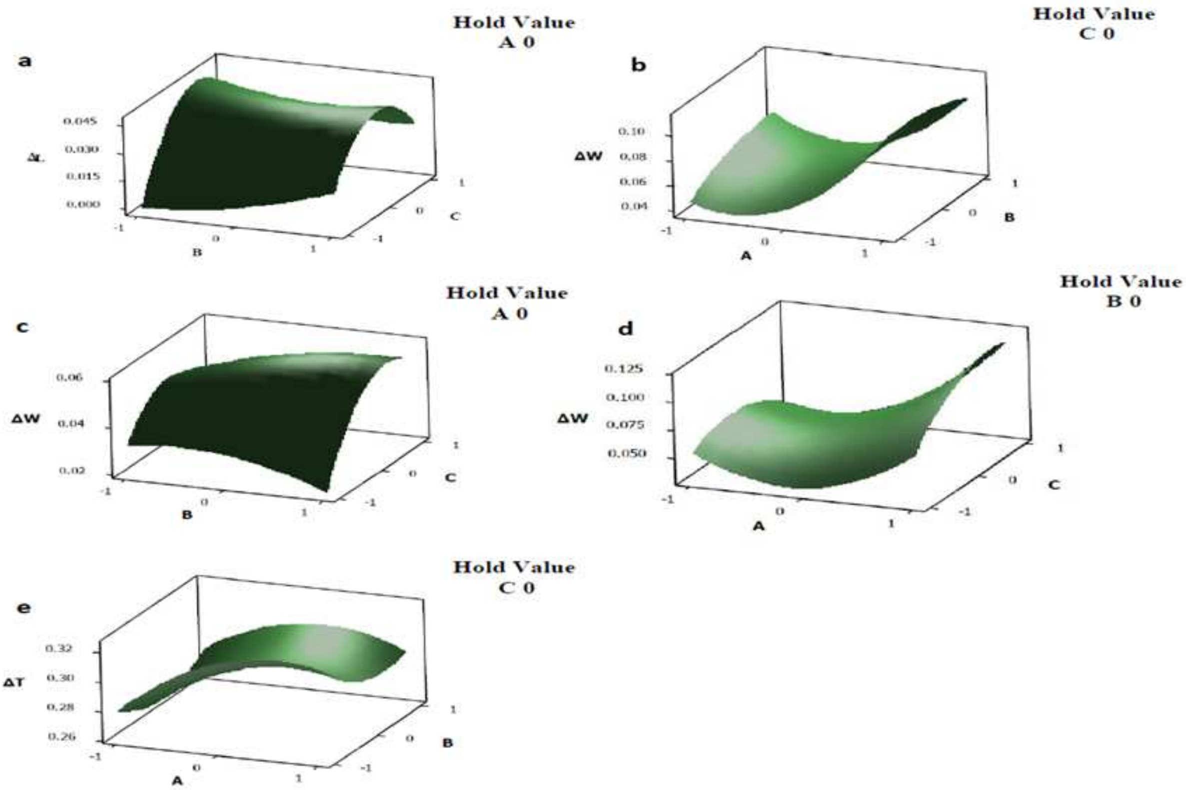

Figure 3: Response Surface Plots for Significant Interaction for Relative Change in Length (ΔL), Relative Change in Width (ΔW) and Relative Change in Thickness (ΔT)

Once the significance of terms is established then composite desirability is carried out to find the optimal factor setting for minimizing the overall deviations in dimension. The desirability ranges are from zero to one (least to most desirable respectively). The set of conditions possessing highest desirability value is selected as optimum condition for the desired response. Figure 4 (a to c) give the optimal factor setting for minimizing the overall deviation in length (ΔL), breadth (ΔW) and thickness (ΔT) in individual. Figure 5 presents the optimized factor setting for fabricating a single FDM parts with minimum deviation in length (ΔL), breadth (ΔW) and thickness (ΔT). Table 4, presents the optimized process parameter settings in coded form for minimizing the deviation in relative changes in dimensions in individual and in combination.

Table 4: Optimized Process Parameter for Minimizing the Deviation in Relative Changes in Dimensions

Response (Relative Changes in)	Optimized Process Parameters for Minimizing Deviation in Dimensions		
	Raster angle (A)	Air Gap (B)	Raster Width (C)
length (ΔL)	0	-1	-1
Breadth (ΔB)	-1	-1	1
Thickness (ΔT)	-1	-1	-1
Length (ΔL), Breadth (ΔB) and Thickness (ΔT)	0	1	-1

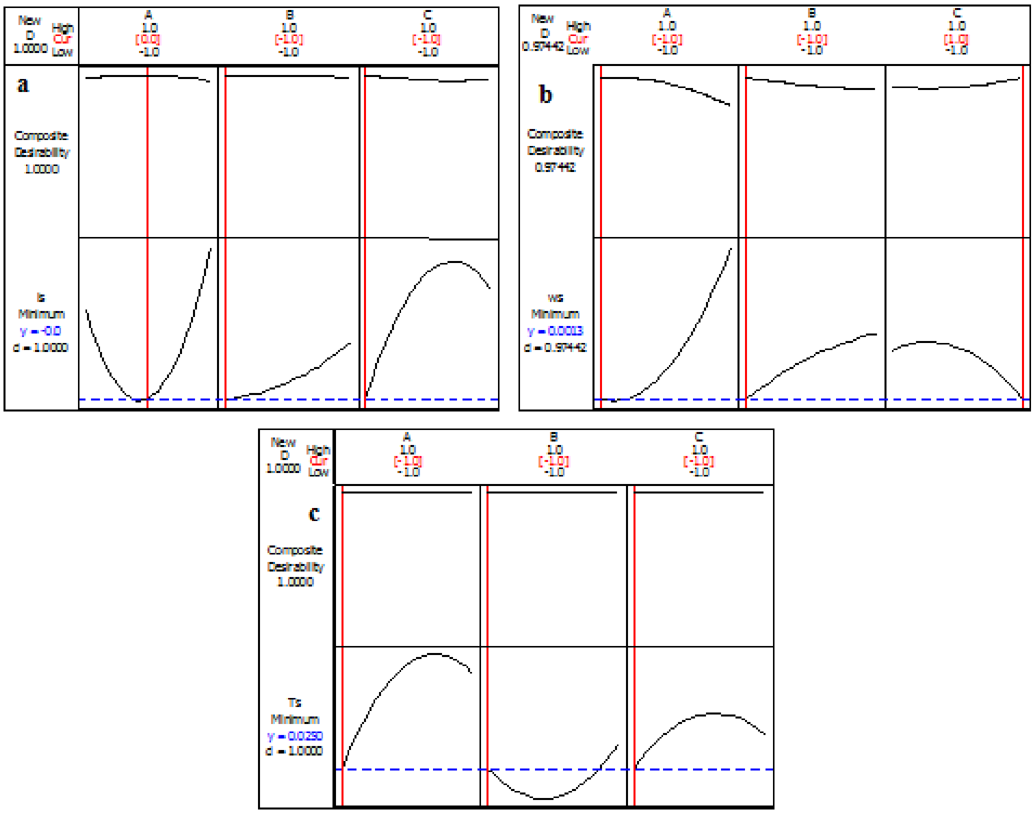

Figure 4: Optimized Process Parameters for Minimizing (a) Relative Change in Length (ΔL), (b) Relative Change in Breadth (ΔB) and (c) Relative Change in Thickness (ΔT)

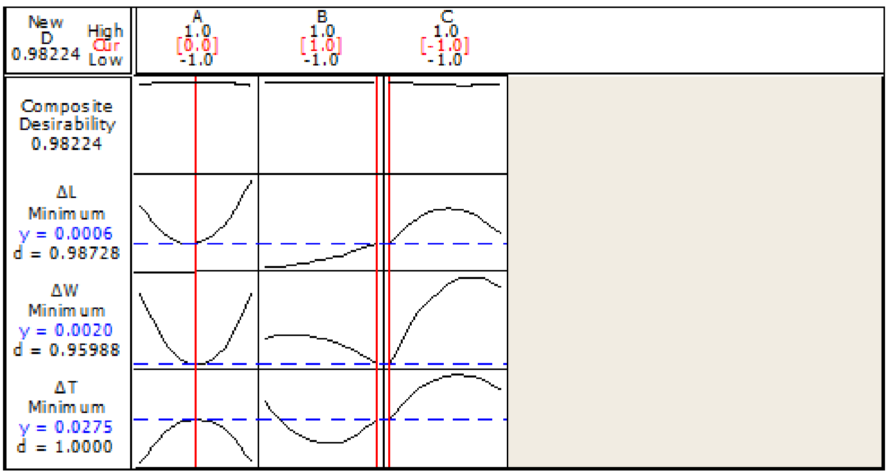

Figure 5: Optimized Process Parameter for Minimizing the Overall Deviation in Dimensions

CONCLUSIONS

In the present work, effect of three factors viz., raster angle, raster to raster gap (air gap) and raster width each at three levels is studied on the dimensional accuracy of FDM build part. Response surface methodology (RSM) coupled with the composite desirability function (CFD) is used to optimize the process parameters to achieve minimum overall deviations i.e. change in length, width and thickness in combined. ANOVA explains the significance of factors and their interaction on accuracy of dimensions. The result shows that dimensional accuracy is mainly affected by raster angle and

raster width and air gap don't impart significant effect on dimensional accuracy. It was also concluded that for minimizing the overall deviation in dimension (relative change in length (ΔL), breadth (ΔW) and thickness (ΔT)) raster angle (30º), maximum air gap (0.004 mm) and minimum raster width (0.4064 mm) is desirable. Thus, it is proposed that fabrication process of FDM parts must be based on optimum settings obtained through a structured methodology to show minimum deviation from actual value.

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